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Comparing the life cycle costs of a traditional and a smart HVAC control system for Australian office buildings

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ABSTRACT

Many smart technologies have been introduced in buildings with the aim to reduce the energy and GHG emissions associated with their operation, particularly through improved control systems for regulating heating, ventilation and air conditioning (HVAC) equipment. Despite their energy saving potential, only a few studies have comprehensively assessed the costs associated with their practical implementation from a life cycle perspective. Accordingly, this study quantifies and compares the life cycle costs of a smart HVAC control system with that of a traditional control system, in the context of an Australian office building. For both systems, the required hardware are specified based on the characteristics of these systems and the layout of the serviced spaces in the reference building. The costs incurred over the period of assessment are quantified using the net present cost (NPC) approach. To evaluate the effects of these control systems on the operational energy costs of the building HVAC system, the control logics of both these systems are modelled through building energy simulations. The results show that, over the period of assessment, the smart control system incurred a higher total cost compared to the traditional control system. However, the findings from the simulations show that the HVAC energy cost savings achieved through the specification of the smart control system offset the additional cost incurred to deploy this system over the traditional control system. The smart control system resulted in HVAC operational cost savings between 9 % and 10 % compared to the traditional control system. Sensitivity analyses indicated that the total life cycle costs varied between −27 % and +50 %, with the discount rate and energy price increase rate being the most influential parameters.

Abbreviations and acronyms

BMS	Building management system
C	Cost
Capex	Initial cost
COP	Coefficient of performance
DR	Discount rate
E	Electricity demand

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EMS	Energy management system
EOL	End-of-life
EP	Energy price increase
G	Natural gas demand
HVAC	Heating, ventilation and air conditioning
ICT	Information and communication technology
IR	Inflation rate
LCA	Life cycle assessment
LCC	Life cycle costing
LCSA	Life cycle sustainability assessment
NPC	Net present cost
Opex	Operational cost
POA	Period of assessment
POG	Price of goods
Q	Quantity
R	Recurring cost
SCADA	Supervisory control and data acquisition
SHGC	Solar heat gain coefficient
SL	Service life
TOU	Time-of-use
VAV	Variable air volume
VM	Virtual machine

Subscripts

c	Control system
computational	Computational resources
electricity	Electricity
gas	Natural gas
h	Hardware
y	Year

Symbols

α	Mathematical operator
δ	Difference in costs
Z^+	Positive integer

1. Introduction

Efforts to reduce the energy consumption and mitigate climate change have become increasingly important in recent years. The building sector is often identified as a high priority in this regard, as it accounts for approximately 30 % of the energy consumed as well as 26 % of the global greenhouse gas (GHG) emissions globally [1]. Heating, ventilation and air conditioning (HVAC) is typically the largest contributor to the building operational energy and GHG emissions in commercial buildings [2,3]. Much effort has been devoted to reducing the consumption of energy related to the operation of HVAC systems through the development and implementation of innovative systems and tools [4,5].

The Energy Performance of Buildings Directive (EPBD) introduced the concept of 'smart buildings' to promote the deployment of smart technologies in buildings within countries in the European Union [6]. These buildings are described as being able to 'sense, interpret, communicate, and actively respond to changing conditions in relation to (i) the operation of technical systems; (ii) the external environment (including energy grids); (iii) and occupant demands' resulting in optimised energy use, automatic diagnosis and maintenance predictions, and improved occupant comfort [7]. To enable these 'smart building' functionalities, novel information and communication technologies (ICT) such as the Internet of Things (IoT) based sensors and actuators, data-driven control approaches and cloud computing resources are needed [8,9]. The application of ICT for the purpose of automation and control of HVAC systems have been demonstrated in many studies [10–15].

While many studies have reported the benefits of such smart technologies for the automation and control of HVAC systems, limited details have been made available about the hardware implementation [4]. In practice, the decision to invest in these smart technologies is primarily informed by the capital expenditure [16–18]. Scepticisms over the added financial benefits afforded by these technologies over their traditional counterparts further dissuade their acceptance by practitioners and building automation specialists [17]. However, a lower initial investment may not necessarily be optimal from a whole life-cycle perspective, if all the cost structures that arise throughout the building life are not well understood [16,19]. With this background, this paper aims to assess and compare the life cycle costs of a traditional and smart HVAC control system in an office building. Comparing the costs incurred over the life of these systems provides a better understanding of financial benefits, or lack thereof, of smart HVAC control systems over traditional control systems.

2. Background

2.1. HVAC control systems

In buildings, the HVAC control system is responsible for monitoring and controlling the operation of HVAC equipment to ensure that occupants are provided with adequate thermal comfort and indoor air quality conditions. To fulfil this functionality, the HVAC control system, which forms part of the building management system (BMS), relies on a collection of interlinked devices such as sensors, actuators, controllers, operator-system interfaces as well as cables and network hardware [20–22]. The HVAC control system is decomposed into a hierarchy of levels, which consists of local and supervisory controls, respectively. The local level control system is based on a control loop involving a controller, sensors, actuators and controlled devices (e.g., fan, motor, valve, damper, etc.). At each time interval, the state or value of a controlled variable is inferred by a sensor, which then communicates this information to a controller. By comparing this state or value with a desired setpoint, the controller identifies the appropriate response and sends decision signals to the actuator. Upon receiving the signal from the controller, the actuator changes the operating parameters in the controlled devices such that the controlled variable is returned to the desired setpoint. These control loop steps are then repeated over the next time interval [23]. The supervisory controller functions as a superordinate system to the local controller, hence, dictates the operating logic of the latter [24]. At this level, control decisions about the HVAC equipment operation are made, such as turning the cooling or heating system 'ON' and 'OFF' based on a pre-set daily expected occupancy schedule, or the hours during which a building is in use.

Although these traditional control systems have been shown to give satisfactory performance, they may not necessarily be optimal due to their limited ability to interact with the internal and external environments [25]. These systems are typically based on time-of-day based fixed operating schedules, suggesting that they do not account for sources of disturbances such as occupancy and weather. Some studies have reported the substandard performance of traditional control systems in buildings with high thermal inertia envelopes and systems [25,26] as well as in control scenarios involving non-linear processes with large time lags [27,28]. The mismatch between the pre-determined operating schedules and real-time dynamics of the environments within which the HVAC equipment operate has been shown to contribute to energy wastage [29].

In order to overcome some of the shortcomings of traditional control systems, many smart control techniques have been proposed in the literature [30,31]. These smart control techniques have been shown to be able to account for disturbances from building occupants, weather conditions, as well as changes in electricity price signals in the decision-making process, and respond to these changes in a manner that minimises operational energy and cost of the HVAC system while maintaining the desired thermal comfort and indoor air quality [25,32]. As these smart control systems are rooted in novel computing methods, which includes model-based predictive control (MPC), learning based methods, and agent-based systems, they typically need the availability of the relevant actionable information to determine the suitable control responses.

2.2. Quantifying the costs associated with HVAC control systems

Smart control systems rely on the deployment of a wide range of sensors in the serviced spaces within a building to gather information about the indoor environmental conditions, occupancy and power consumption. Ambient sensors such as temperature, humidity, air velocity, volatile organic compound (VOC), carbon dioxide (CO_2), and particulate matter (PM) sensors collect information about the indoor environmental conditions, while passive infrared (PIR), ultrasonic and microwave sensors indicate the presence or absence of occupants based on their movements [33]. Changes that occur in ambient conditions have also been suggested as an alternative approach to inferentially measure the occupancy level [34–37]. The deployment of additional sensors, and consequently the increased volume of data generated, means that additional computing and data storage resources are required for smart control systems. For traditional control systems, the lower computational requirements of simpler rule-based algorithms are usual met by means of computing and data storage hardware of the BMS. Conversely, due to the demand-responsive nature of smart control system algorithms, a larger amount of computing power and data storage is required, which is satisfied by means of either a dedicated server or cloud-computing solutions [25].

These resources requirements suggest not only higher capital costs, but also increased operational and recurring costs. The deployment of smart HVAC control systems over their traditional counterparts is only justified when the financial benefit is demonstrated. In the context of the building sector, the requirement for high investment has been a deterrent to the implementation of energy efficiency measures, particularly if the energy savings during the operational phase of the building fails to recover the initial investment. Moreover, the perception of high-risk associated with the challenges in estimating real and unforeseeable costs of advanced technologies as well as the variations in energy costs further discourages investment into these technologies, even if the estimates of energy savings are high [38].

One approach to assess the economic performance of a product or system is life cycle costing (LCC). Life cycle costing is described as a technique to assess 'all costs associated with the life cycle of a product that are directly covered by the main producer or user in the product life cycle' [39]. In effect, life cycle costing allows for the quantification of all costs and revenues of a product or system incurred over a specified period of time [40,41]. This technique also forms the basis of the life cycle sustainability assessment (LCSA) framework, which combines LCC with the environmental life cycle assessment (LCA) and social life cycle assessment (S-LCA), for a comprehensive sustainability assessment [42]. Specifically for the building and construction sector, LCC has been shown to be a useful method for assessing and comparing the effectiveness of energy efficiency measures [38,43]. A voluntary standard which proposes an

LCC framework that is applicable to the building and construction sector is ISO 15686 [44,45]. Here, LCC is referred to as 'technique which enables comparative assessments to be made over a specified period of time, taking into account all relevant factors, both in terms of initial costs and future operational costs' [44]. In practical terms, the LCC framework outlined in this standard consists of four steps, which are the (i) definition of alternative strategies to be assessed; (ii) selection of the economic criteria; (iii) acquisition and grouping of significant costs; and (iv) performance of a risk assessment (sensitivity analysis) [45].

Pertaining to HVAC control systems, only a few studies have assessed the cost incurred to deploy HVAC control systems [46]. In Hagström et al. [16], the authors compared the life cycle costs of individual, zone and central-level control while taking into account the economic implications of the loss of occupant productivity resulting from these control levels. The authors in Bird et al. [4] quantified the capital expenditure and costs savings resulting from the implementation of MPC for HVAC control in a food-retail building and reported that the cost to implement their proposed control system far exceeded the cost savings over a period of two months. The authors also suggested the variability of the MPC system to other factors such as the attributes of the HVAC system and the building envelope's thermal characteristics. Clearly, there is a lack of studies that comprehensively assess the life cycle costs of smart HVAC control systems, as well as the benefits or lack thereof, provided by these systems.

3. Research approach

This section describes the design and deployment of different HVAC control system configurations to inform the quantification and comparison of the life cycle costs. The HVAC control system configurations used in this study are based on Gobinath et al. [47], which assessed the life cycle energy and GHG emissions of these systems. A summary of the steps involved in the design, deployment and cost comparison of the HVAC control systems is shown in Fig. 1.

3.1. Reference building

The quantification of the life cycle costs of the control systems is performed in relation to a reference building that is representative of typical Australian office buildings. Offices form 23 % of the Australian commercial building stock with approximately half categorised as mid-tier office buildings [48]. Mid-tier office buildings are defined as having floor areas of less than 10000 m^2 as well as equipped with HVAC systems consisting of a combination of central plants and split units [48]. In this study, an existing office building in Melbourne is adapted to define and model the reference building, complying with the size requirements of a typical mid-tier Australian office building. The reference building comprises four storeys, with a total floor area of 6000 m^2. In order to satisfy the functional requirements of an office building, the necessary type and quantity of spaces was specified for this reference building, which then enabled the design and deployment of the traditional and smart control system hardware.

The HVAC energy needs, and subsequently operating costs, of the reference building is dependent on the climate. Climate effects is an important consideration for energy studies of built environment based in Australia, given the categorisation of the climate

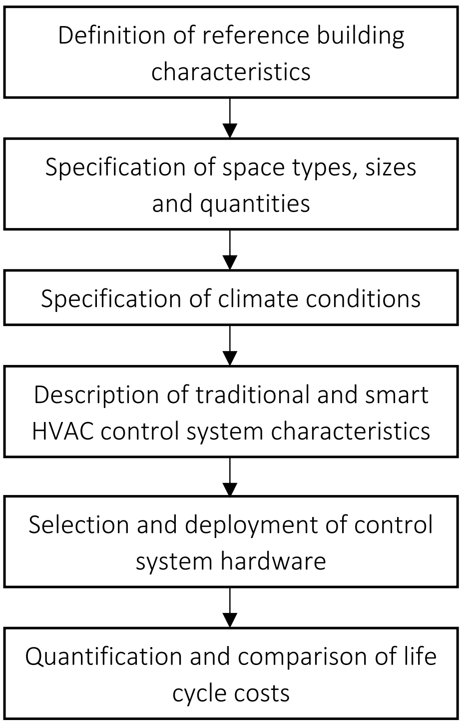

Fig. 1. Design, deployment and cost comparison of traditional and smart HVAC control systems.

conditions into eight distinct zones [49]. In this study, the effects of the differences in climate conditions are included in the analysis by specifying two scenarios, which are the regions of Melbourne and Brisbane. The climates of Melbourne and Brisbane are designated as Cfb and Cfa in the Köppen–Geiger climate classification system, respectively [50]. Wider diurnal temperature swings and lower levels of humidity are characteristic of the mild temperate climate of Melbourne, which is in contrast to the humid subtropical climate of Brisbane. In Brisbane, the monthly lowest temperatures vary between 6 and 7 °C higher than in Melbourne [51]. These differences result in variances between the operational costs of buildings located in these two regions, since the climate conditions directly affect the magnitude and share of the heating, cooling, equipment, fan and pump energy use. To account for these climate effects, the reference building was assumed to be situated within the central business districts of Melbourne and Brisbane, where most office buildings are found.

3.2. Design of traditional and smart HVAC control systems

To quantify the life cycle costs of both the traditional and smart control systems, the characteristics of these systems are defined, which includes the specification of control effectuation as well as the requirements and deployment of hardware. The traditional control system is characterised as being based on a fixed, pre-programmed, time-of-day operating schedule. This implementation comprises of a host of field-level devices (i.e., sensors and actuators) which communicate with the automation level (i.e., zone controllers), which in turn communicates with the management-level (i.e., operator workstation). Communication between hardware across the control system hierarchy is achieved through a wired network backbone. At the field-level, conditioned rooms are equipped with basic thermostats with simple functions such as ON/OFF, temperature and fan speed selection.

In contrast to the traditional control system, the smart control system 'actively reacts to the thermal comfort and indoor air quality requirements as well as the level of occupancy' in the conditioned spaces. To enable such functionalities, the field-level comprises the necessary sensors to acquire these information. Despite the application of many different sensors for HVAC control, only ambient (i.e., temperature, humidity, and CO_2 level) sensors are deployed in this study, representative of the most commonly reported sensor types for HVAC applications in the literature [29]. The suitability of occupancy sensors for lighting control have been demonstrated in the literature. However, they are ineffective for the control of HVAC systems, owing to their limited ability to count the number of occupants as well as the slow dynamics of HVAC systems, hence, have been excluded in this study [33].

In additional to the differences in the hardware deployed between the traditional and smart control systems, a further distinction is made with regards to the choice of communication media and computing resources. For the smart control system, the field-level devices exchange information by means of wireless communication whilst the computing resources to perform management-level tasks are satisfied through cloud computing. The rationale for these choices is the cost effectiveness and ease of deployment of wireless communication for large number of devices as well as the suitability of cloud computing for control purposes considering the increasing use of IP protocols and the Internet [52].

To calculate the costs of cloud computing services, an analysis for the network traffic is needed. While measurements of actual network traffic flows is possible for real-life control systems, access to such systems are often limited, with researchers relying on testbed experiments, simulations and traces from other environments for traffic data [53]. Moreover, obtaining these flow traffic data from experiments and simulations have limitations given the difficulty for such sources to accurately reflect the behaviour of the real system. Considering these challenges, the traffic flow is estimated in this study instead, taking into account the characteristics of these flows.

Unlike traditional information technology networks, traffic flow data in supervisory control and data acquisition (SCADA) networks have been shown to possess unique characteristics such as being stable over time and non-self-similar, as well as having limited diurnal trends [52]. In SCADA networks, the nodes are less likely to connect and disconnect from the main network while the sensed information is inferred periodically through polling mechanisms [52,53]. In terms of the size of the traffic data, a study by Ndonda and Sadre [53] reported the limited size of network packets (i.e., less than 170 bytes) through an analysis of the traffic traces in an HVAC system in a university building, which is preferred in SCADA protocols typically employed in applications pertaining to BMS. Similarly, Krejčí et al. [54] proposed a framework for monitoring and measuring traffic in BMS and reported the presence of a large number of small packet size flows. Contrary to Barbosa et al. [52] and Ndonda and Sadre [53], however, Krejčí et al. [54]suggested the influence of human activity on the characteristics of the traffic flows, referring to the presence of diurnal patterns in their monitored traffic flows. In this study, an estimation of network traffic is performed considering the characteristics of such flows that were identified in the literature, hence, allows for the calculation of the costs incurred to implement the cloud-based smart control system. Here, it is assumed that sensors acquire information periodically through a polling mechanism at a fixed time-interval with minimal occupant influence (i.e., absent diurnal patterns). Furthermore, an average network package size and duration per poll is assumed for each device, to estimate the amount of data generated and transferred by each device, which is then aggregated to the control system level [55].

3.3. Hardware requirements and deployment of HVAC control systems

The design and deployment of the hardware needed for both traditional and smart control systems is described in this section. The traditional control system was specified based on the location and layout of individual conditioned spaces and the characteristics of the system identified, which then allowed for the field-level sensors and actuators to be deployed. Subsequently, the zone-level controllers, floor-level controllers, operator workstation as well as wired communication network were specified to complete the system. In practical implementations, the possibility of future expansion is accounted for by allowing for redundancies, however, such consideration was excluded for simplicity.

The deployment of the smart system included the hardware needed to measure and record the indoor environmental quality variables of interest, which enables the system to be actively respond to changes in these variables. For instance, to vary the rate of mechanical ventilation in conditioned spaces based on the level of occupancy (inferred from measurements of the CO_2 level), CO_2 sensors were specified in these zones. Similar to the traditional system, the hardware required for the smart control system was specified using the location and layout of individual conditioned zones as well as the characteristics of the control system. For large, open spaces without walls or partitions, the hardware was spatially distributed evenly, while for smaller, enclosed spaces, dedicated hardware was fitted [56].

The communication network of smart control system consists of a combination of both wired and wireless communication, in contrast to the wired media based traditional system. The application of radio-frequency based wireless communication network and cloud computing for the smart control system was enabled by the specification of auxiliary hardware such as routers and gateways. The router is described as a device which 'enables communication between two or more networks' whilst the gateway 'enables communication between two different communication protocols' [57]. In this implementation, only the field-level hardware (i.e., sensors and zone-level controllers) were equipped with wireless communication, whereas the automation and management-level hardware were assumed to be communicate through wired means. This distinction is attributed to the cost effectiveness of the wired communication media for hardware occupying higher levels in the control system hierarchy. To complete the specification of the smart control system, the locations and distances between routers were specified such that the attenuation of signal strengths due to the transmission of radio-frequency waves through obstructions such as walls, floors, doors, etc. do not severely affect communication stability [56,58]. The arrangements of both the traditional and smart control systems at the floor level are shown in Fig. 2.

4. Quantifying life cycle costs of HVAC control systems

4.1. Goal and scope

The aim of this life cycle costing study is to quantify and compare the life cycle costs of a traditional and smart HVAC control system in the reference building. The functional unit is defined as the hardware and operational resources requirements of the HVAC control systems over a period of 50 years. The perspective of the building owner is considered, hence, only cost structures relevant to this stakeholder are considered. The effect of deploying both HVAC control systems on the costs incurred to operate the HVAC system is also included in the analysis to allow for the comparison between these two control systems.

4.2. Life cycle cost inventory

The life cycle costs of both the traditional and smart HVAC control systems can be categorised into the initial, recurring, operational and end-of-life costs. The calculation methods and sources of cost data used are detailed in the following sections.

4.2.1. Initial and recurring capital costs

The capital costs for deploying both the traditional and smart HVAC control system hardware were calculated based on prices

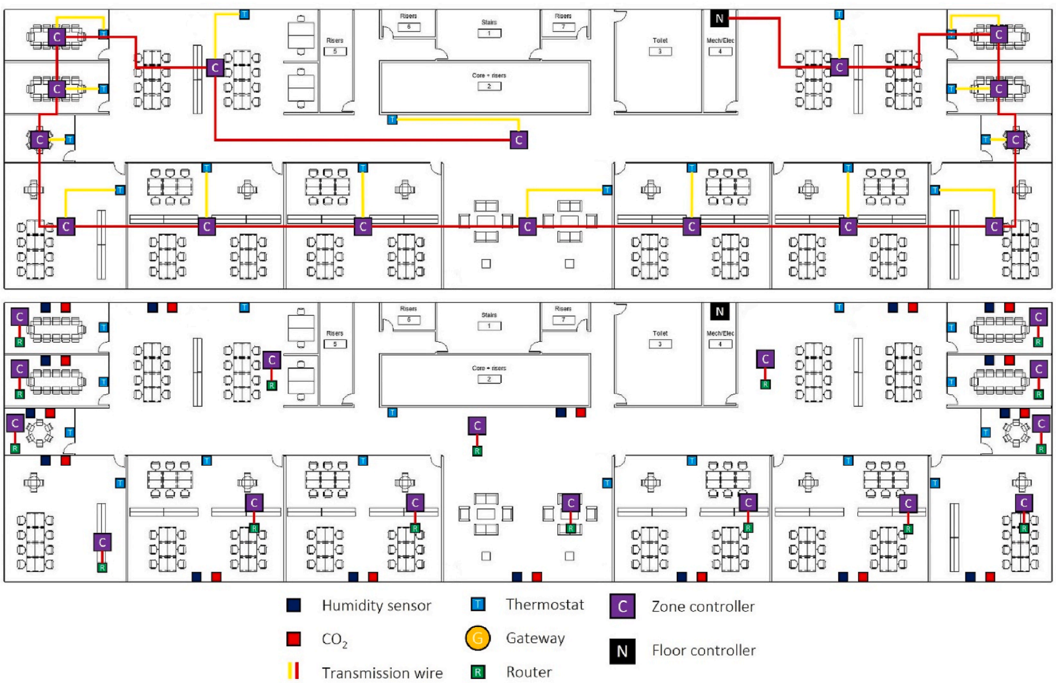

Fig. 2. Deployment scenario for traditional (top) and smart (bottom) control scenario.

provided by local suppliers in the year 2022. In the event where the cost of a hardware item was not made available by suppliers, estimations were made based on prices quoted in the Australian Construction Handbook [59].

Since the hardware used in both the traditional and smart HVAC control systems have shorter useful service lives relative to the assumed period of assessment, they are expected to be replaced several times during the period of assessment. These replacements include part of a subcomponent (e.g., battery) or the whole hardware item (e.g., sensor). The estimated service lives of the hardware items considered were established based on IEA 4E [60]. The costs incurred to replace these hardware items were calculated as per Equations (1) and (2).

$$R_{c,y} = \sum_{h=1}^{H} \alpha_{h,y} \times Q_h \times C_h \tag{1}$$

$$\alpha_{h,y} = \left(0 \text{ } if \text{ } \frac{y}{SL_h} \neq Z^+\right) \text{ } or \text{ } \left(1 \text{ } if \text{ } \frac{y}{SL_h} = Z^+\right) \tag{2}$$

where $R_{c,y}$ is the recurring costs for year y (A\$), Q_h is the number of hardware items h, C_h is the cost of hardware h (A\$), SL_h is the service life of hardware h, and Z^+ refers to positive integers. This means that the recurring costs incurred as a result of hardware replacements were indexed based on the year these hardware were replaced over the period of assessment.

4.2.2. Operational costs

The annual operational costs associated with control systems were calculated based on the cost of electricity to operate the hardware as well as the costs associated with the additional resources needed for computations and data storage, as per Equation (3).

$$\mathrm{Opex}_{c,y} = C_{\mathrm{electricity}} \times \sum_{h=1}^{H} E_{h,y} \times Q_h + C_{\mathrm{computional}} \tag{3}$$

where $\mathrm{Opex}_{c,y}$ is the operational costs for year y (A\$), $C_{electricity}$ is the price of electricity (A\$/kWh), E_h is the electrical energy consumed by hardware h (kWh), Q_h is the number of hardware items h, and $C_{computional}$ is the cost associated with external computing and storage resources (i.e., cloud) (A\$). The distinctions between the costs incurred during the operational phase of both the traditional and smart control systems are described in Sections 4.2.2.1 and 4.2.2.2.

4.2.2.1. Operational costs of building-level hardware. For both the traditional and smart control systems, the operational energy was calculated as the sum of energy needs for individual hardware within these systems. These energy needs were obtained by multiplying the hardware' rated power by the period of operation. Most of the hardware used for controlling HVAC systems are typically equipped with a range of energy saving mechanisms which include sleep/wakeup schemes, data reduction techniques as well as radio communication and routing optimisation. These approaches lead to reduced operational energy, and hence, the cost incurred [61–63]. In this study, however, a worst case scenario was considered, in which each hardware item was assumed to operate at its maximum rated power at all times (i.e., 24 h per day). Electricity tariffs for large commercial buildings, comprising fixed, peak demand and volumetric charge components, were obtained from a local distribution network service provider, Ergon [64] as shown in Table 1. This multi-part tariff structure is most commonly applied to large commercial energy users, who have separate energy network contracts with the distribution network service provider [65,66].

4.2.2.2. Operational costs of cloud computing resources. The computational resource requirements of the smart control system was assumed to be met by means of cloud computing services. Estimating the cost associated with cloud computing services is not straightforward, owing to the types of services provided as well as the pricing models employed. For instance, through a literature review, Altmann and Kashef [67] identified 21 cost factors categorised into six groups for Infrastructure-*as*-a-Service (IaaS) cloud services. Ellman et al. [68] proposed a costing model for cloud services which combines computation, storage, memory and networking charges, while Buell and Collofello [69] considered costs associated with processing, storage, bandwidth and additional services in their analysis of transaction level costs in the context of Software-*as*-a-Service (SaaS) and Platform-*as*-a-Service (PaaS). While costing models have been proposed, performing cost analysis can often be challenging as they require detailed information about the hardware, load levels as well as the intended applications. The difficulty in measuring the actual resources consumed, compounded by the deployment options chosen for an application as well as possible changes in the pricing schemes of service providers, makes it rather challenging to accurately estimate cloud service costs [67,70,71].

In this study, the cost of cloud computing services was estimated using the cost calculator of a service provider. Within the private cloud services industry, Amazon Web Services (AWS), Microsoft Azure and Google Cloud Platform (GCP) make up the largest providers of cloud services, with each accounting for approximately 31 %, 9 % and 4 % of the total market share [68]. Each service provider offer differentiated pricing models, hence, like-for-like comparisons are not always possible [72]. For simplicity, the cost was calculated using the AWS Pricing Calculator [73] based on the following assumptions.

Table 1
Electricity tariff.

Tariff component	Cost unit	Cost
Fixed	A\$/day	392.46970
Demand (peak hours)	A\$/kW/month	23.34970
Volumetric	A\$/kWh	0.20571

a) The total annual data was calculated as the sum of the annual data generated per device, as described in Section 3.2.
b) Only a single virtual machine (VM) was used, with 2 cores. This assumption was based on the distribution of virtual machines from actual monitored traces, where the majority of VMs contain two cores as opposed to 4, 8, 24 or more cores [72]. The VM was also assumed to be fully utilised throughout the period of assessment (i.e., approximately 720 h per month).
c) The memory used was assumed to be 8 GB, which represents the most commonly used memory allocation [72]. The cost for storage was determined based on the monthly volume of data generated.
d) Although most service providers provide the option for reserved instance (i.e., the VM is paid for in advance for one or more years' of services) for discounted prices, a worst case scenario was assumed, with the service charge paid on a monthly basis.
e) Networking costs are not charged within the pricing structure of AWS, hence, were not included in this analysis [68,73].

A suitable VM that fulfils these requirements was chosen, which allowed the monthly, and subsequently the annual cloud computing costs to be calculated.

4.2.3. End-of-life costs

The hardware used in the control systems was assumed to have no residual value when they are replaced at the end of their useful life. Similarly, hardware with non-zero useful service life at the end of the analysis period was also assumed to be disposed, and hence, have a residual value of nil. According to Morris and Metternicht [74], the treatment of waste electrical and electronic equipment (WEEE) in Australia is dictated by key legislations such as the National Waste Policy [75], Product Stewardship Act 2011 [76], Product Stewardship (Televisions and Computers) Regulations 2011 [77], and National Television and Computer Recycling scheme 2011 (NTCRS) [77]. In effect, WEEE are dismantled and sorted within suitable facilities in Australia before they are processed further, both domestically or internationally. In this study, the cost for the end-of-life treatment was calculated based on quotes provided by a WEEE recycling service provider based in Australia [78]. To account for the transportation cost, the distance of travel between the modelled location of the reference building and the recycling facility was multiplied by the haulage costs provided in the Australian Construction Handbook [59].

4.2.4. Effects of the choice of control systems on building HVAC energy costs

Quantification of the effects of both the traditional and smart control systems on the building operational HVAC costs, and hence the cost benefits or lack thereof, was based on building energy simulations. Using the EnergyPlus™ software, a building energy model that is identical geometrically to the modelled reference building was developed and the control logics of both the traditional and smart control systems were simulated. To be representative of an Australian office building, the building envelope was specified to meet the minimum energy efficiency requirements stipulated in Section J of the Building Code of Australia for Class 5 (office) buildings [49]. The main input parameters for the envelope elements and glazing are provided in Table 2 and Table 3, respectively.

Inputs pertaining to the operation of the building such as the daily operating hours, occupancy, indoor air temperature, relative humidity, and load schedules such as lighting, appliances, and occupancy, were specified in the EnergyPlus™ Input Data File (IDF). Values for these inputs were selected based on Section J of the Building Code of Australia for Class 5 (office) buildings [49]. The metabolic rate was specified to reflect the average level of activity in an office setting [79,80]. A summary of these parameters are detailed in Table 4.

The building energy model was specified with a HVAC system, which was a rooftop variable-air-volume (VAV) system with hot water reheat, owing to their suitability for commercial use to meet the indoor air quality and thermal comfort requirements [81,82]. In this HVAC configuration, the circulating hot and cold water loops fulfilled the heating and cooling demands of the reference building, respectively; a boiler was specified to generate the heating medium, while a water-cooled chiller generated the cooling medium. For heating, a natural gas-based condensing boiler with a nominal efficiency of 0.89 was assumed, which varied according to the part-load ratio and the leaving water temperature. Cooling needs were met through a water-cooled chiller with a nominal coefficient of performance (COP) of 5.5; this COP was modelled to vary as a function of the part-load ratio as well as the leaving chilled water and entering condenser fluid temperatures. In addition to the heating and cooling, mechanical ventilation was also provided to introduce fresh outdoor air into the conditioned spaces. The heating, cooling and ventilation requirements are dependent on various sources of sensible and latent heat related to occupancy, artificial lighting, as well as appliances and equipment, however, identical load schedules were specified for both the traditional and smart scenarios to enable cost comparisons to be performed. Considering the differences in the climates of Melbourne and Brisbane together with the internal loads, the sizing of boiler, chiller, cooling tower, as well as fans and pumps were determined.

The effects of the traditional and smart control systems on the operational HVAC costs were quantified by simulating two control logics, each representing the traditional and smart HVAC control systems, respectively. The time-of-day based operating schedules of the traditional control system were implemented through fixed setpoint temperature profiles and predetermined hourly volumetric ventilation air flow rates. The ventilation rate was calculated as the sum of the minimum ventilation rate per person multiplied by the

Table 2
Input parameter values for building envelope.

Envelope element	Thermal transmittance (U-value) (W/m^2K)
Ground floor	0.300
Roof	0.086
Wall	0.324

Table 3
Input parameter values for glazing.

Glazing parameters	Value
Window-wall ratio	0.45
U-value (W/m^2K)	1.960
SHGC	0.691

Table 4
Simulation input parameter values.

Parameter	Value
Operating hour (hrs)	7:00–18:00 on weekdays
Occupant density (m^2/person)	10
Metabolic rate (met)	1.2
Temperature range (°C)	21–24
Relative humidity range (%)	30–60
Lighting power (W/m^2 per 100 lux)	4.5
Appliances and equipment (W/m^2)	11

maximum level of occupancy, reflecting the traditional approach to mechanical ventilation [83]. Fig. 3 shows the daily heating and cooling temperature setpoints for a weekday.

A demand responsive control logic based on the types of sensors deployed for the smart control system was implemented. EnergyPlus™ Runtime Language (ERL), which is an in-built programming language to define and manage the Energy Management System (EMS) control programmes, was used to specify and implement the control logic for the smart control system. The EMS programme assigns the indoor air temperature of each controlled zone as a sensor, and the heating and cooling temperature setpoints as actuators. For each simulation timestep (i.e., 15 min), the indoor air temperature is measured and compared with the setpoint temperatures and deadband range to decide if the current heating and cooling setpoints should be maintained. When the indoor air temperature is within the heating and cooling temperature setpoints, the controller turns OFF the heating and cooling by reducing the heating setpoint and cooling setpoint to a very low and very high value, respectively. This allows the indoor air temperature to drift until the setpoint limits are exceeded. In addition to these temperature setpoint changes, the air flow rate is also set to zero, which in effect turns the fan OFF. Conversely, the controller turns ON the heating and cooling by restoring both the heating and cooling setpoints as well as the air flow rate to their original values in the event the indoor air temperature falls outside the deadband range.

The smart control system was also specified with a control logic that dynamically varies the volumetric flow rates of mechanical ventilation depending on the measured indoor CO_2 concentration level. Owing to its practicality for measuring the indoor air quality as well as inferentially estimating the level of occupancy, the CO_2 concentration level was chosen as the determinant for mechanical ventilation rates [83]. The EMS enabled demand-controlled ventilation by varying the mechanical ventilation volumetric air flow rate proportionally to the measured indoor CO_2 concentration level at each simulation interval. The purpose of deploying humidity sensors for the smart control system was limited to the measurement and regulation of thermal comfort level, since they do not affect the heating and cooling energy, hence operational costs. The reason for this designation is the limited usefulness of the relative humidity for the control of energy consumption [84,85].

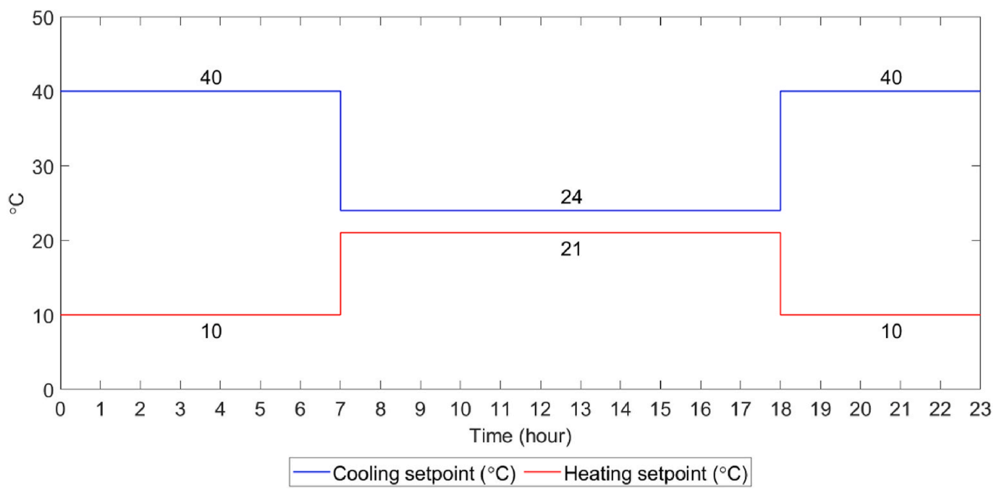

Fig. 3. Time-of-day based cooling and heating setpoint schedule.

The annual costs attributed to the operation of HVAC systems was calculated as per Equation (4).

$$\text{Opex}_{\text{HVAC,y}} = \text{C}_{\text{electricity}} \times \text{E}_{\text{HVAC,y}} + \text{C}_{\text{gas}} \times \text{G}_{\text{HVAC,y}} \tag{4}$$

where $\text{Opex}_{\text{HVAC,y}}$ is HVAC system operational costs for year y (A$), $\text{C}_{\text{electricity}}$ is the price of electricity (A$/kWh), $\text{E}_{\text{HVAC,y}}$ is the electricity demand of the HVAC system for year y (kWh), C_{gas} is the price of natural gas (A$/MJ), and $\text{G}_{\text{HVAC,y}}$ is the natural gas demand of the HVAC system (MJ). Prices for natural gas were obtained from Energy Australia [86], which consists of fixed and time-of-use (TOU) volumetric declining block components. The electricity tariffs used are shown in Table 1, while the natural gas tariff is detailed in Table 5.

4.3. Life cycle cost assessment

The calculation of life cycle costs can be performed through two main approaches, which are discounted flow analysis and payback analysis. Discounted flow analysis can be further categorised into net present cost (NPC) and internal rate of return (IRR) methods. In this study, the life cycle costs were calculated in NPV terms, as this approach avoids the inability of payback analysis to account for monetary flows that occur beyond the payback period as well as the risk of computing multiple or non-existent compound discount rates when applying the IRR method [87]. The NPC of both the traditional and smart control systems were calculated as per Equation (5).

$$NPC_c = Capex_c + \sum\nolimits_{y=0}^{POA} \frac{\left(Opex_{c,y} + R_{c,y} + EOL_{c,y}\right) \times (1 + IR)^y}{(1 + DR)^y} \tag{5}$$

where NPC_c is the net present cost of control system c over the period of assessment (A$), Capex_c is the capital costs for control system c (A$), $\text{Opex}_{\text{c,y}}$ is the operational costs for year y (A$), $\text{R}_{\text{c,y}}$ is the recurring costs for year y (A$), $\text{EOL}_{\text{c,y}}$ is the end-of-life costs for year y (A$), IR is the inflation rate, DR is the discount rate, and POA is the period of assessment in years.

The quantification of the life cycle costs through the NPC method requires the specification of cost variables such as the period of assessment, inflation and discount rate. Past life cycle costing studies pertaining to HVAC and control systems have used assessment periods less than 25 years [16,88]. However, in this study, an assessment period of 50 years was assumed, which is typical of studies focused on building systems [43,89–91]. The inflation rate of 3 % was assumed considering trends in price changes over the past 10–15 years, while a discount rate of 6 % was chosen to reflect the conditions in Australia [43,88].

5. Results and discussion

5.1. Life cycle costs of HVAC control systems

The life cycle costs of the HVAC control systems, over a period of 50 years, are summarised in Table 6. For both systems, the recurring capital costs accounted for the largest share of the total costs, followed by the initial capital costs. This is due to the relatively short useful life of the control system hardware compared to the building service life, meaning the former is replaced several times over the assumed period of assessment. Operational and end-of-life phases contributed relatively little to the total life cycle costs.

The differences in the initial and recurring capital costs between the traditional and smart control systems are due to the increased types and quantities of hardware needed to meet the functional requirements of the smart control system. For the operational phase of the control systems, the increase in cost for the smart control system relative to the traditional system was attributed to cloud computing services, in addition to the increased quantity of hardware.

5.2. Operational costs of HVAC system

The differences between the total costs to operate the heating and cooling equipment as well as the distribution and delivery fans and pumps are shown in Fig. 4. In general, the cost of electricity contributed to the largest share of the total operational costs for the HVAC system. A major contributing factor to this high cost of electricity is the larger share of cooling energy delivered to the reference building compared the heating energy needs. As the Melbourne climate is characterised as having a higher number of heating degree days, relative to Brisbane, more heating was provided in the reference building based in Melbourne.

5.3. Net cost of smart control system

A comparison of the total costs incurred, in net present cost (NPC) terms, was performed to determine whether or not the deployment of the smart control system resulted in an overall cost benefit. The operational costs of the HVAC system are larger than the life cycle costs of the control systems by several orders of magnitude, as shown in Fig. 5. The payback period of the additional cost

Table 5
Natural gas tariff.

Tariff component	Cost unit	Value
Fixed	A$/day	1.342
Volumetric (TOU): 0-50	A$/MJ	0.044528
Volumetric (TOU): 50-550	A$/MJ	0.036168
Volumetric (TOU): 550-1370	A$/MJ	0.03278
Volumetric (TOU) > 1370	A$/MJ	0.028325

Table 6
Net present costs of traditional and smart HVAC control systems.

Scenario	Net present cost, A$ (%)			
	Initial capital	Recurring capital	Operational	End-of-life
Traditional (Melbourne)	57,554 (32.1)	105,831 (59.1)	14,803 (8.3)	152 (0.5)
Smart (Melbourne)	102,370 (24.7)	270,849 (65.3)	37,103 (9.0)	1027.2 (1.0)
Traditional (Brisbane)	57,554 (32.2)	105831.5 (59.3)	14,803 (8.3)	136 (0.4)
Smart (Brisbane)	102,370 (24.7)	270,849 (65.4)	37,103 (9.0)	921 (0.9)

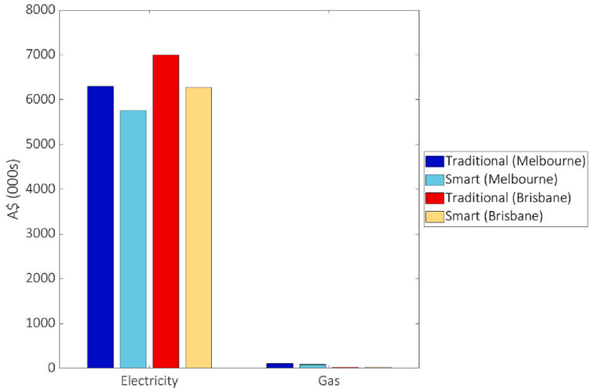

Fig. 4. Operational costs of the HVAC systems.

incurred to deploy the smart control system over the traditional system that is offset by the HVAC operational cost savings was estimated to occur at the end of the third and second year in the case of Melbourne and Brisbane, respectively (see Fig. 6). This difference between payback periods between Melbourne and Brisbane is primarily due to the higher operational energy costs, hence higher savings, in the case of the latter. In summary, operational HVAC cost savings of approximately 9 % and 10 % were obtained in the case of Melbourne and Brisbane, respectively, over a period of 50 years.

5.4. Sensitivity analyses

The results of the life cycle cost study are subject to uncertainties associated with the cost variables and energy price trends [5,43,92]. To examine the effects of these uncertainties on the robustness of the results, sensitivity analyses were undertaken. The key cost variables that have been considered in this study, which represent the most influential and frequently used in life cycle costing studies [43], are shown in Table 7.

Discount rates have been shown to be the most influential parameter in studies pertaining to building energy efficiency studies [5,38]. Various discount rates have been employed in previous life cycle costing studies, ranging from as low as 0 % [93] to as high as 15 % [89]. In this study, the discount rate was varied between 3 % and 9 %. The variation in discount rates was also coupled with a commensurate variation in inflation rates of between 2 and 4%, as suggested by Leckner and Zmeureanu [94] and Stephan and Stephan [89]. Based on the modelled discount and inflation rates, the total life cycle cost, which includes both the life cycle cost of the control system and the operational cost of the HVAC system, varied between −27 % and +50 % for both control systems, as shown in Fig. 7.

The effect of energy price increases has been accounted for in the analysis through the specification of a rate of inflation. However, the rate at which the energy price increases annually may not necessarily follow the evolution trends in the general inflation rate. In Stephan and Stephan [89], Copiello and Bonifaci [95] and Na et al. [88], the authors decoupled energy price increased from the general inflation rate, and specified different energy inflation rates in their analysis. In a similar approach, two annual energy price

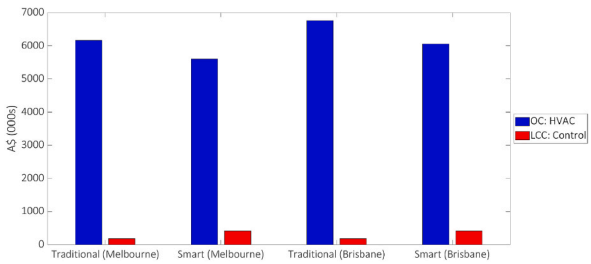

Fig. 5. Comparison between the HVAC operational costs (OC) and the control system life cycle costs (LCC).

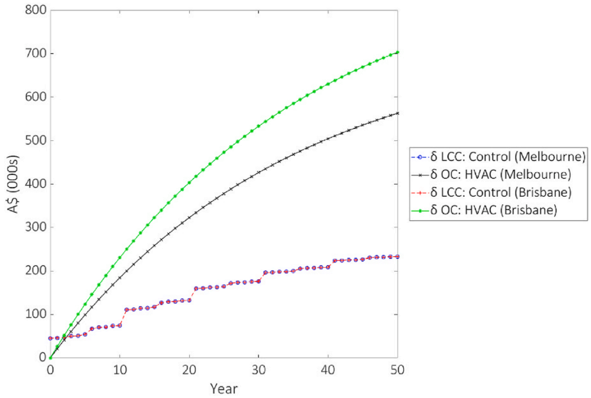

Fig. 6. Cumulative HVAC operational cost savings (δ OC) vs. additional costs incurred to deploy the smart control system (δ LCC).

Table 7
Variables for sensitivity analyses.

Cost variable	Base scenario	Alternative scenario
Discount rate (DR)	6 %	±3 %
Inflation rate (IR)	3 %	±1 %
Energy price increase (EP)	3 %	±2 %
Price of goods (POG)	–	±10 %
Period of assessment (POA)	50 years	±25 years

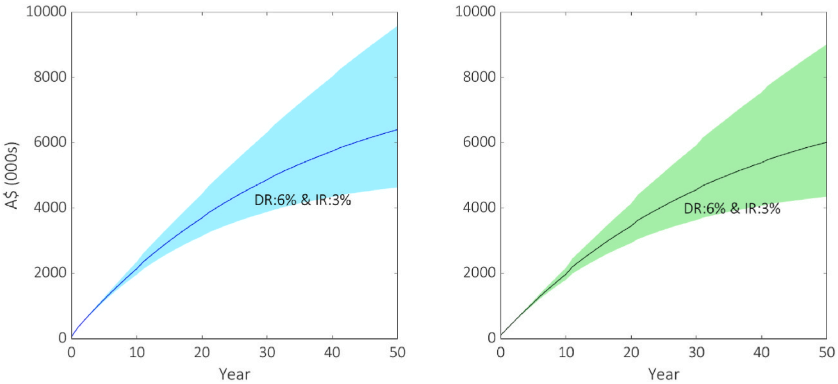

Fig. 7. Variability of total life cycle cost of the traditional (left) and smart (right) control systems with discount (±3 %) and inflation (±1 %) rates.

increase rates have been applied, which represent a change of ±2 % over the general inflation rate; in both scenarios, the discount rate was maintained at 6 %. Changing the energy price increase rate resulted in a deviation of between −27 % and +50 % in the total life cycle cost (see Fig. 8).

Varying the price of goods also resulted in a variation in the total life cycle cost, although only to a small extent. For example, by increasing and decreasing the price of goods by 10 %, the total life cycle cost only varied by approximately 0.3 % and 0.6 % for the traditional and smart HVAC control systems, respectively. This is due to the relatively lower cost to deploy and replace the control hardware compared to the cost of energy used over the period of assessment. Similarly, the period of assessment also had a minimal effect on the results since the payback period of the additional cost to implement the smart control system over the traditional control system was much shorter than the building service life as well as the useful life of the hardware. These findings are consistent with the results from other studies assessing the financial impacts of energy-saving measures, where the discount rate and energy price evolution were found to be the most influential parameters [96–98].

5.5. Limitations and further research

There are a number of limitations stemming from this study. Firstly, the evolution of costs with the development of technology was only partially assessed through sensitivity analysis. Several studies have alluded to trends in cost reductions for IoT-based HVAC control hardware [9,99,100] as well as the variability of retail electricity prices for industrial consumers in Australia [101], meaning that further thorough investigation into the effects of two key cost parameters, namely, the price of goods and the energy price increase

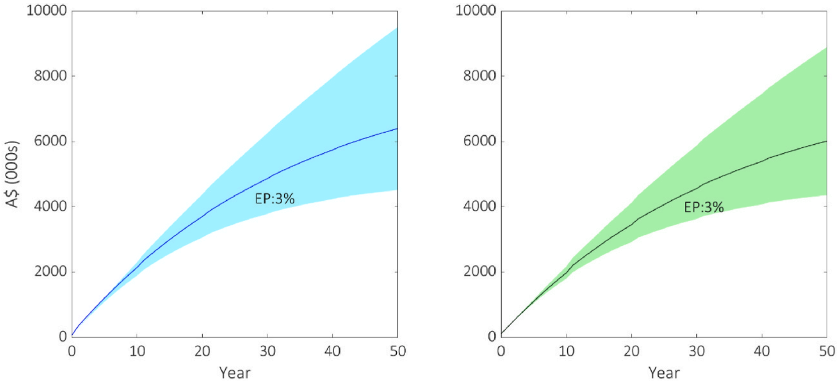

Fig. 8. Variability of total cost of the traditional (left) and smart (right) control systems with energy price increase rates (±2 %).

rate, is warranted when more detailed information becomes available. Secondly, the approach that was used to calculate the cost associated with cloud computing resources depended on several assumptions about the volume of data and types of resources used (e.g., VM and memory). This is due to the limitations associated with approaches to reliably estimate the volume of network traffic in the absence of measured data. The cost associated with cloud computing may have been inflated, as approximately 45 % of the expenditures on cloud resources are typically not utilised [72]. With more reliable data, additional sensitivity analysis may be performed to assess the influence of data transferred into and from the cloud, as well as the server and storage usage on the costs incurred [67]. Despite these limitations, this study offers an insight into the cost benefits of deploying a smart HVAC control system over a traditional control system, considering the costs incurred over the life of a building.

The results of this study are valid only for this reference building, as there are various other approaches to smart control that have been reported in the literature [25,32]. Further research is needed to assess the financial implications of deploying different advanced control systems with additional information requirements, and hence, hardware requirements. Examples include image-based occupancy detection sensing techniques [102–105] as well as approaches which require the deployment of local weather stations [106,107]. In addition to energy cost savings, smart HVAC control systems are also capable of providing other beneficial features such as the detection of anomalies and faults in the operation of HVAC systems, which would also lead to further cost savings [108]. However, such a feature has not been included in this study, thus, it is suggested for further investigation.

6. Conclusions

In this study, the life cycle costs of a traditional and smart HVAC control system were assessed and compared, in the context of an office building. Firstly, by identifying the characteristics of both the traditional and smart control system, the hardware required were chosen and deployed in a simulated reference building. Using the net present cost method, the life cycle costs of both these systems were calculated for a period of assessment of 50 years. To assess the benefits of the smart control system, the costs of electricity and gas resulting from the control logics of both systems were determined through an energy simulation of the building HVAC system. Differences in climate conditions, and their effect on the operational costs for heating, cooling and ventilation, were accounted for by modelling two distinct climate zones in Australia. The main findings are as follows.

a) The life cycle cost of the smart control system was significantly higher than that of the traditional system, mainly due to the capital expenditures occurring during the initial and recurring (i.e., replacement) phases.
b) The smart control system, with an indoor air temperature based ON/OFF mechanism as well as mechanical ventilation control scheme based on the CO_2 concentration level, resulted in HVAC operational cost reductions of 9 % and 10 % for the building located in Melbourne and Brisbane, respectively.
c) Sensitivity analyses showed that the discount rate and energy price increase rate were the most influential parameters affecting the total life cycle costs incurred, with variability between −27 % and +50 %.

In summary, by comparing the operational HVAC cost savings of the smart control system with the increase in the life cycle costs incurred to deploy this system, relative to the traditional system, this study demonstrated a net benefit to deploying the smart control system.

CRediT authorship contribution statement

Praddeep Gobinath: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Robert H. Crawford:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Marzia Traverso:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Behzad Rismanchi:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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